Clinical Decision Support Today & Tomorrow

What does the future have for us?

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Potential conflict of interest

- Canadian Society of Anesthesiologists
- Michael Smith Foundation
- NSERC
- CIHR
- Research Draeger Medical
- Consultant GE Medical



Phases of Innovation

- It will never work
- It worked in animals but will never work in humans
- It worked in a small selected group of patients
- It worked in a large group but required special expertise or is too expensive
- Of course it works. I came up with the idea but did not bother to publish it.

Delivery of Fastanll main backing store for the 418/III. Capacity 132MB. London Hospital 1970

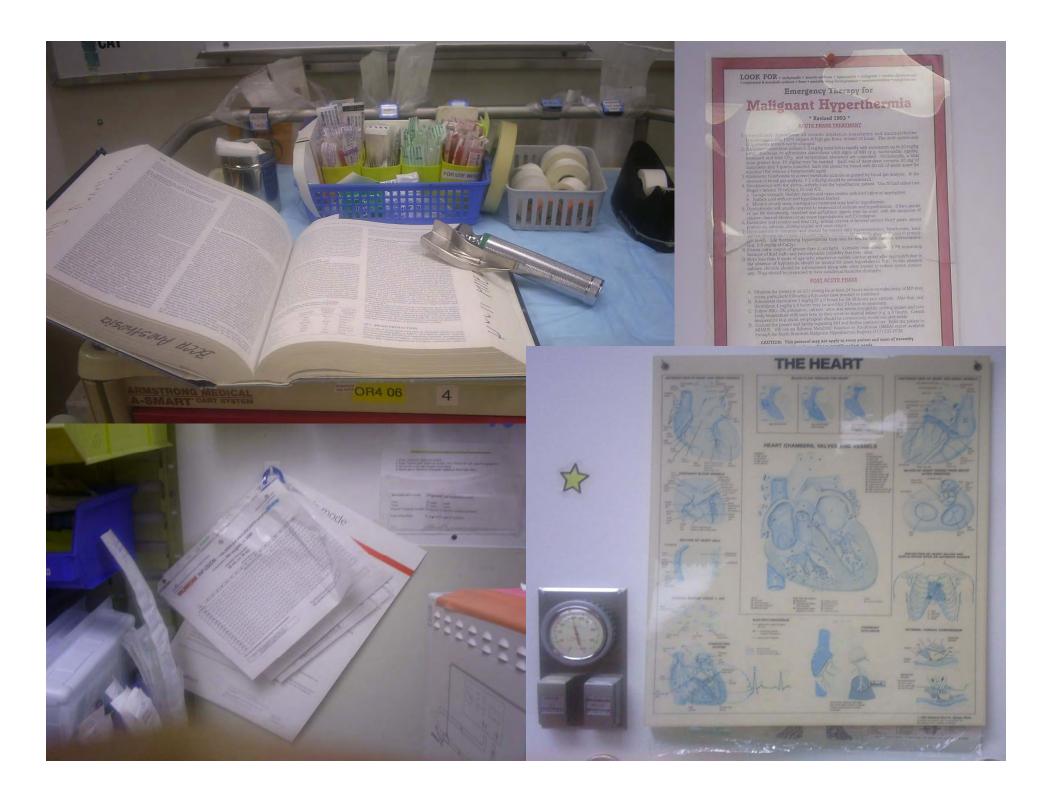


Who wants clinical decision support?

- Do you use clinical decision support?
- Do you want clinical decision support?
- Why do you want clinical decision support?

What is decision support?





Clinical Decision Support

 Clinical Decision Support is a clinical system, document, application or process that helps health professionals make clinical decisions to enhance patient care.

Decision support in clinical monitoring

- Alerting
- Reminding
- Suggesting
- Critiquing
- Interpreting
- Diagnosing
- Predicting
- Doing!



What are we good at?

Your job is secure!

- Value judgments
- High complexity
- Adaptation to context
- High reliability
- Interdependence

What can we do better?

- Cognitive bias
- Information overload
- Changing habits
- Repetitive tasks
- Attention prioritization
- Multiple simultaneous tasks

Diagnostic Error

- 40 000 to 80 000 US hospital deaths result from misdiagnosis annually
- 9% TIA's missed
- 5% MI's missed
- Preoperative antibiotics
- These are NOT bad people...

Leape LL, Berwick DM, Bates DW. Counting deaths due to medical errors JAMA. 2002;288(19):2405

Newman-Toker DE Pronovost PJ. Diagnostic Errors - The Next Frontier for Patient Safety. JAMA. 2009;301(10):1060-1062

"The greatest obstacle to knowledge is not ignorance, it is the illusion of knowledge"

Daniel Boorstein

Adverse Anecdote

- Level IV evidence
- Last bad experience
- Expert opinion

Stuebe AM. The New England journal of medicine. 2011 Jul 7;365(1):8–9

Choice (Decision) Blindness



(Johansson, 2000)

Two Minds when making decisions

System 1 Intuition

Fast

Parallel

Automatic

Effortless

Associative

Emotional

Slow learning

2X4

System 2 Reasoning

Slow

Serial

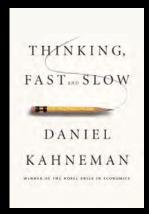
Controlled

Effortful

Rule Governed

Neutral

Flexible



17X25

Heuristics are used to reduce mental effort in decision making, but they may lead to systematic biases or errors in judgment.

- Representativeness heuristic
 - insensitive to base rate/ prior probabilities
 - strong inference from small sample
 - confuse 'normal' and 'rare' events
- Availability heuristic
- Anchoring and adjustment
- Decision framing

Heuristics are used to reduce mental effort in decision making, but they may lead to systematic biases or errors in judgment.

- Representativeness heuristic
- Availability heuristic
 - swayed by information that is vivid, wellpublicized, or recent
 - correlate events if close together
- Anchoring and adjustment
- Decision framing

Heuristics are used to reduce mental effort in decision making, but they may lead to systematic biases or errors in judgment.

- Representativeness heuristic
- Availability heuristic
- Anchoring and adjustment
 - depends on starting value
 - inadequate adjustment
- Decision framing

Heuristics are used to reduce mental effort in decision making, but they may lead to systematic biases or errors in judgment.

- Representativeness heuristic
- Availability heuristic
- Anchoring and adjustment
- Decision framing
 - prospect theory

Decision making is not rational?

Unrecognized limitations

The unrecognized limits of professional skill help explain why experts are often overconfident

Statistical algorithms greatly outdo humans in noisy environments for two reasons: they are more likely than human judges to detect weakly valid cues and much more likely to maintain a modest level of accuracy by using such cues consistently.

Daniel Kahneman

Detecting changes – Real Time

Real time clinician compared to post hoc review

	PPV	Sensitivity	% Detected
HR	0.75	0.60	59.54
NIBPmean	0.60	0.63	63.33
SpO2	1.00	0.06	6.25
ETCO2	0.74	0.13	12.85
MVexp	0.55	0.11	11.17
RR(CO2)	1.00	0.01	0.94
TOTAL	0.64	0.10	9.54

PPV - positive predictive value

Ansermino, et al.. Anesthesia and Analgesia. 2009;108(3):873-80.

How do we make decisions?

702

Special Article

Defining rules for the identification of critical ventilatory events

[Définition de règles pour identifier les événements respiratoires critiques]

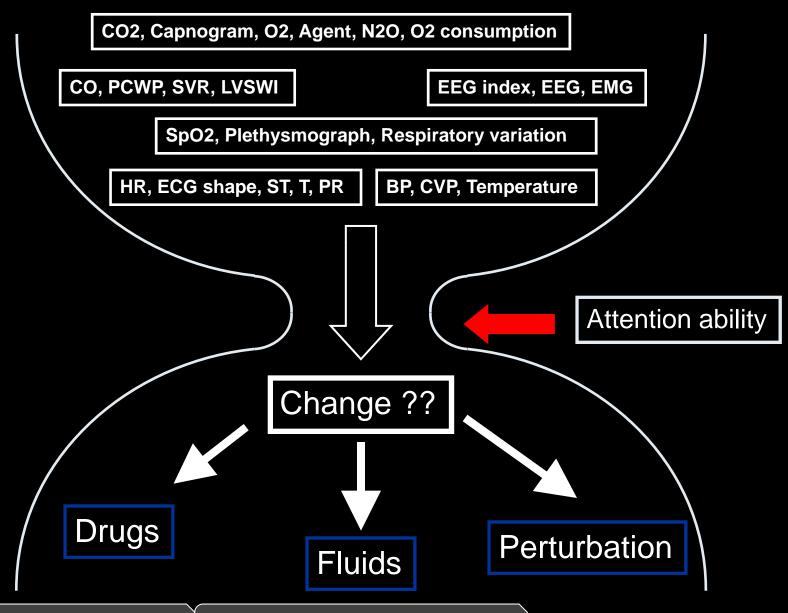
J. Mark Ansermino FRCPC, Maryam Dosani BSC, Erica Amari BA, Peter T. Choi MD FRCPC MSC, Stephan K. W. Schwarz MD PhD FRCPC

What has changed in healthcare?

Information

What will change healthcare?

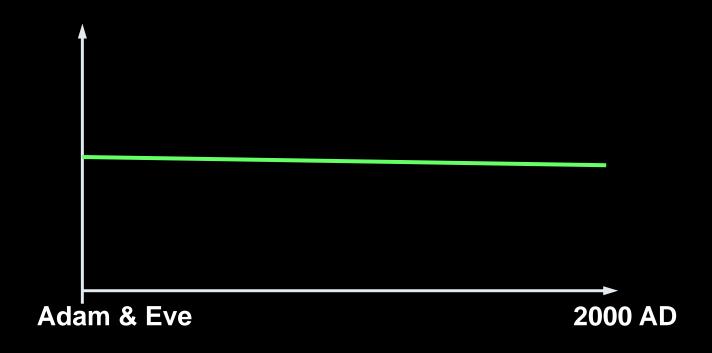
The Human Factor



Cognitive Bias

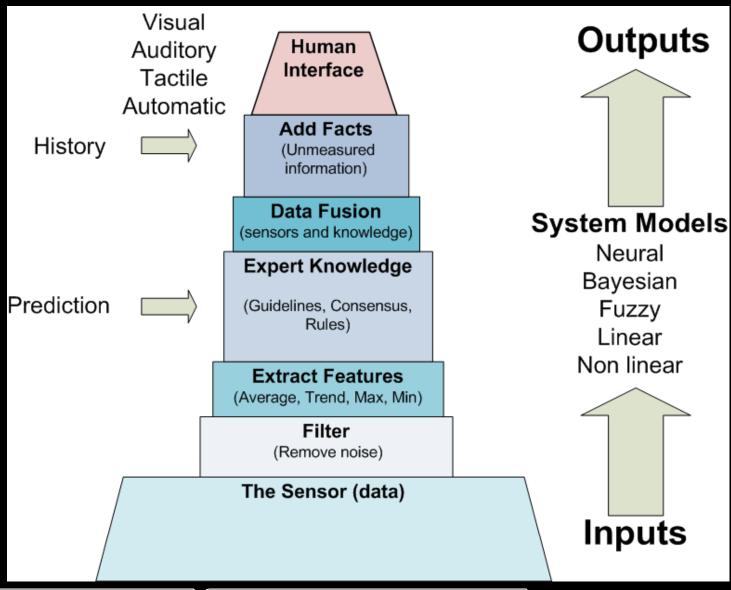
Information Overload

Human Vigilance Over Time

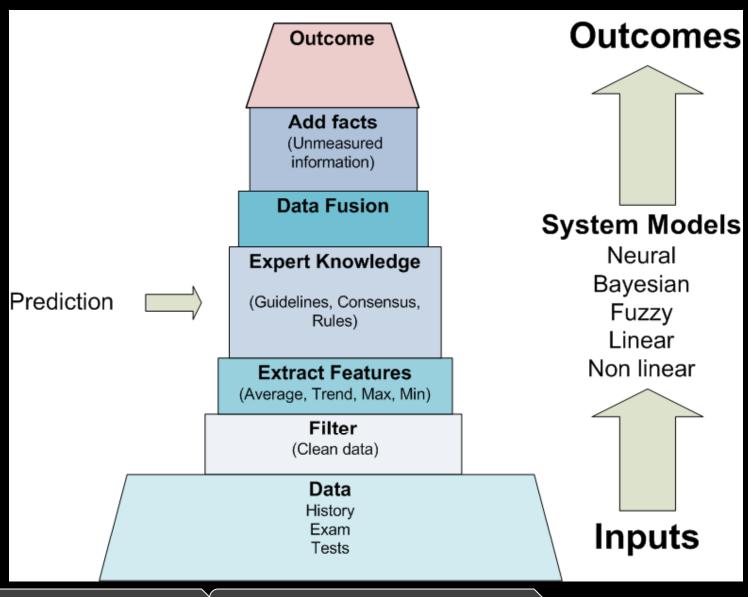


The most precious resource is human vigilance.

The Expert System (sensor)



The Expert System (outcome)



Medicine Based Evidence

Comparative Effectiveness Research

- clinically relevant issues
- who and where were the patients
- what and why were the treatments
- when and how were the outcomes
- assessment of validity and generalizability
 considered together and denoted as accuracy

Context Specific Monitoring

Look at the trend!!

Adaptive feature extraction

Measured signal value





True signal value

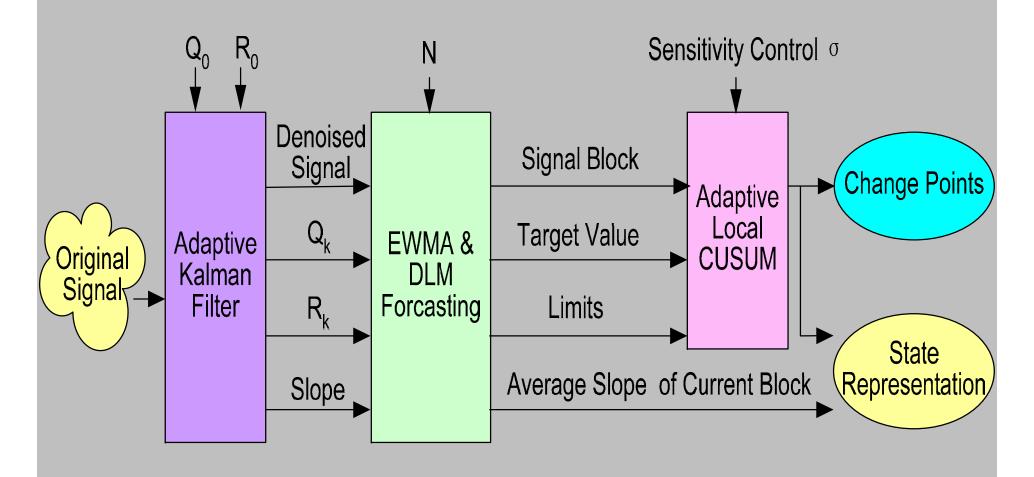




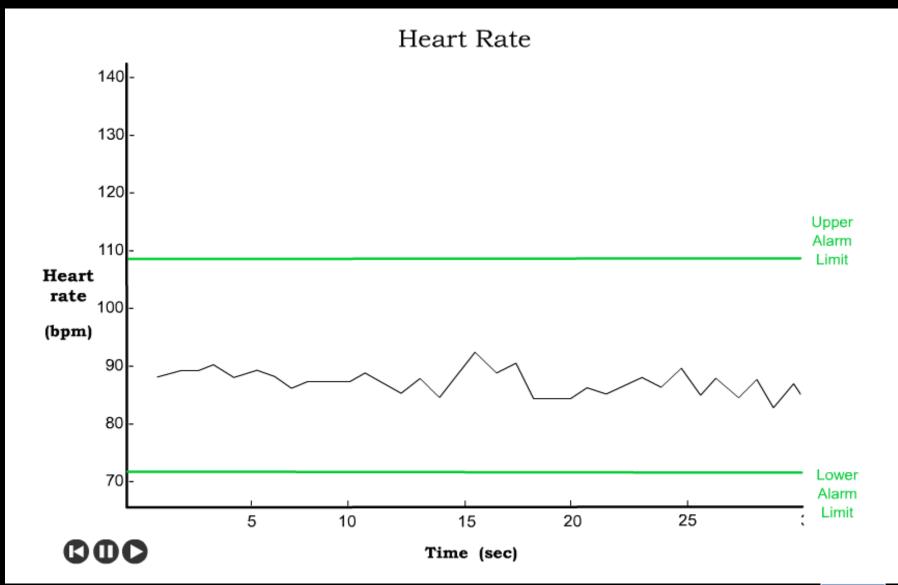
Signal noise

Inter patient and intraoperative variation

Adaptive feature extraction II

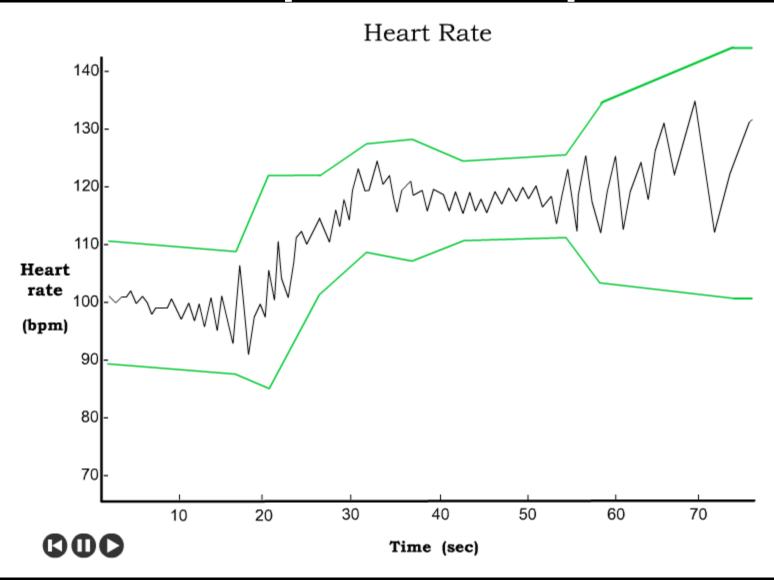


Limit Based Alarms



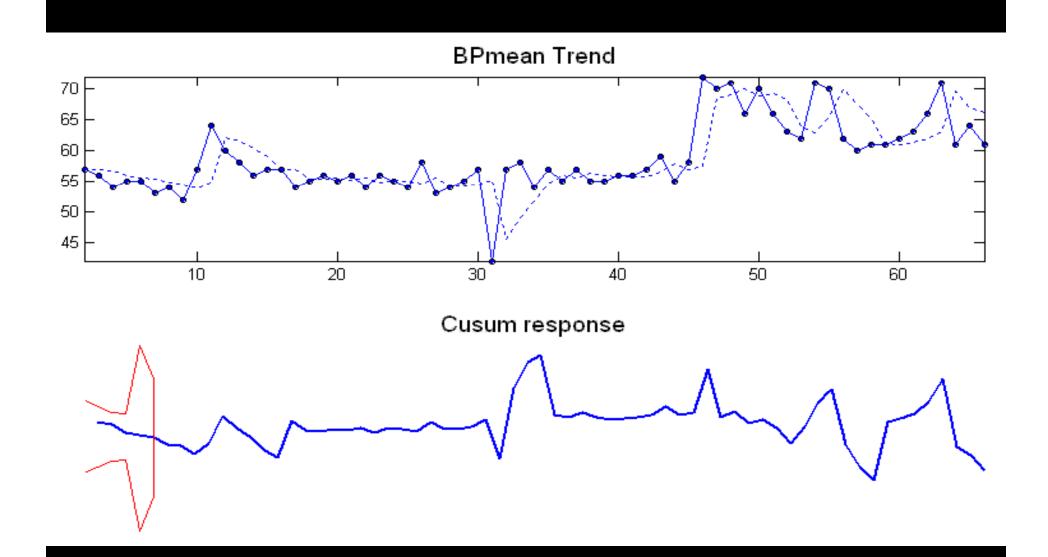


Adaptive Envelope





Change Point Detection - BP



Automated 'change point' detection

- Dependant on full history of the process
- Weighted towards more recent data
- Statistical features continuously updated
- Adaptable to individual patient
- Comparable to visual trend







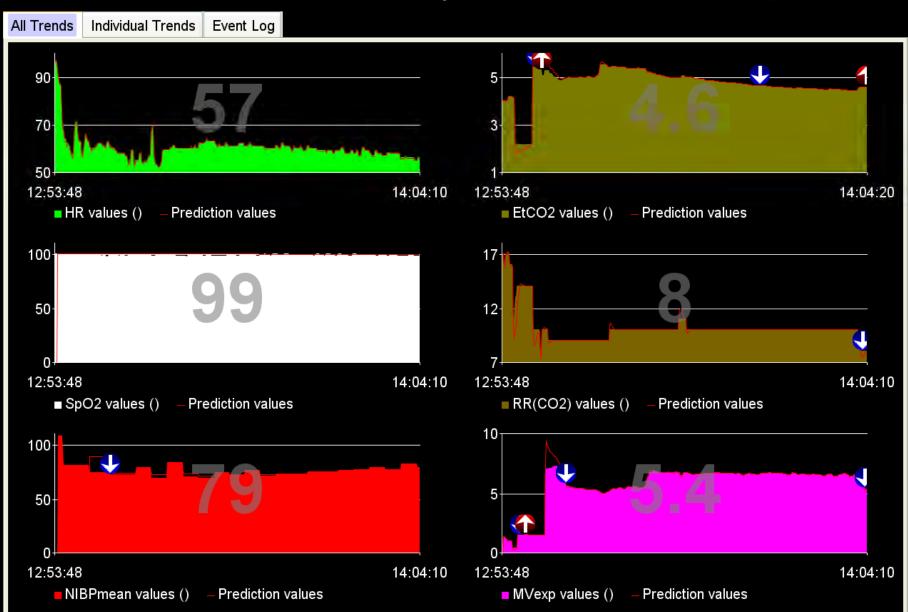




Case Name: Test case



Date/Time: 2006/08/30 14:04:20



Results - Offline

Performance of iAssist compared to post hoc clinician review

	PPV	Events	Missed	Events/h
HR	0.92	297.00	33.00	4.36
NIBPmean	0.94	137.00	10.00	2.01
SpO2	0.98	50.00	0.00	0.73
ETCO2	0.74	249.00	20.00	3.66
MVexp	0.90	230.00	16.00	3.38
RR(CO2)	0.84	128.00	12.00	1.88
TOTAL	0.87	1091.00	91.00	16.02

PPV - positive predictive value

Ansermino, et al.. Anesthesia and Analgesia. 2009;108(3):873-80

Results - On line

Classification of change points per hour of anaesthesia.

15 staff

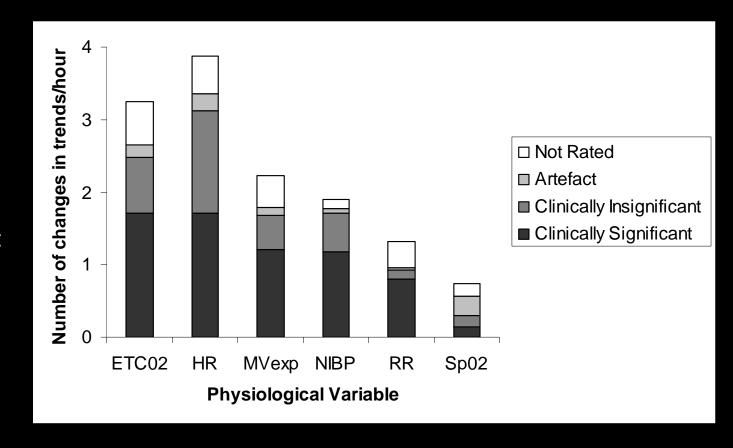
38 cases

103 min

22.8 /case

61% significant

7% artefacts



Dosani M, et al. BJA. 2009;102(5):686-91.

iKnow

Production rules for everyone!

Types of Knowledge

Explicit knowledge

 Can be articulated into formal language, readily transmitted others, easily be processed by a computer.

Tacit knowledge

 Intangible factors embedded in individual experience, such as personal beliefs, and perspective (intuition). Hard to articulate with formal language (hard, but not impossible).

iKnow - knowledge authoring tool



<u>List of possible</u> <u>inputs:</u>

Static representations

Heart rate
Blood pressure
Minute ventilation
Respiratory rate
Electrocautery activated

Dynamic representations

Heart rate increasing
Minute ventilation decreasing
Mean blood pressure 10 min
Heart rate variability
Systolic pressure variation

Rules:

If ... then

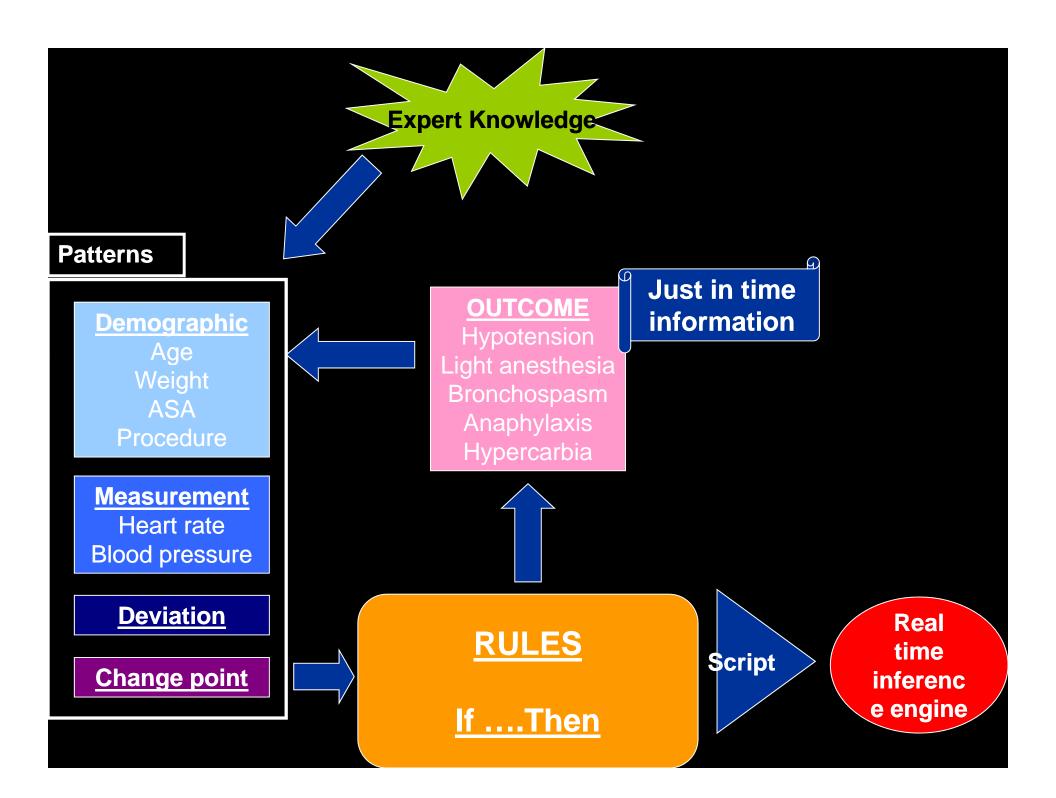
and ... or greater than... less than

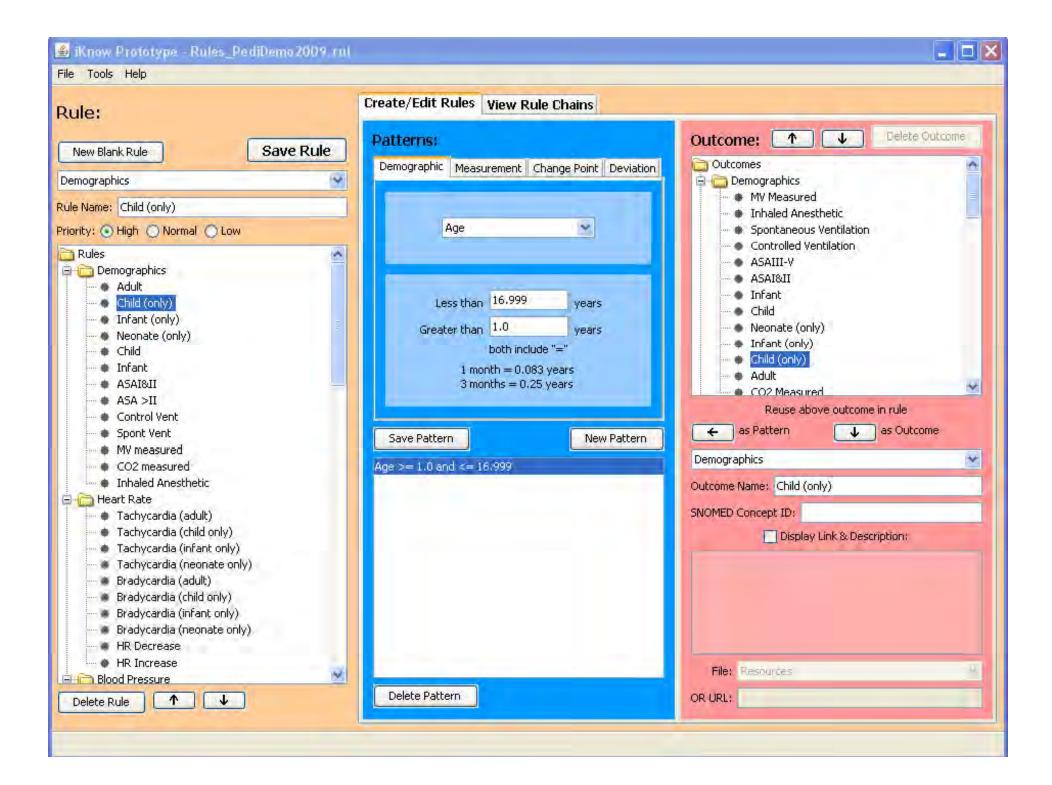
<u>List of possible</u> <u>outputs:</u>

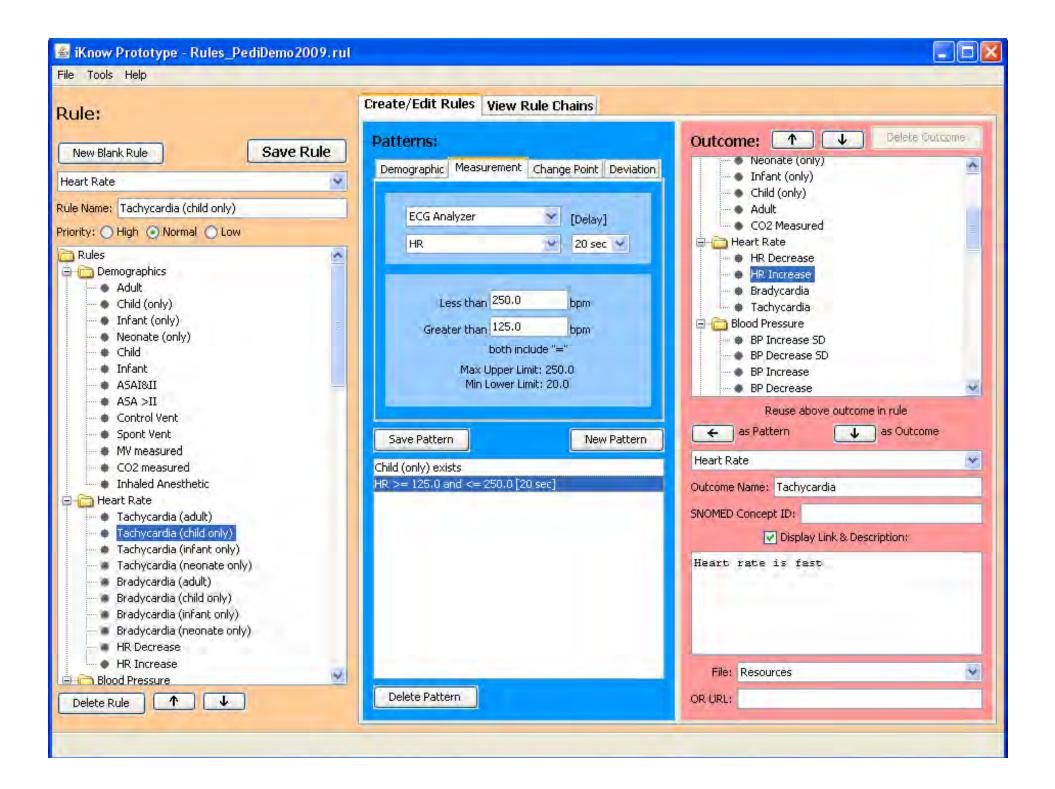
Hypotension
Light anesthesia
Bronchospasm
Circuit leak
Circuit disconnect
Anesthetic overdose
Myocardial ischemia
Hyperthermia
Pulmonary embolism
Main stem intubation
Anaphylaxis

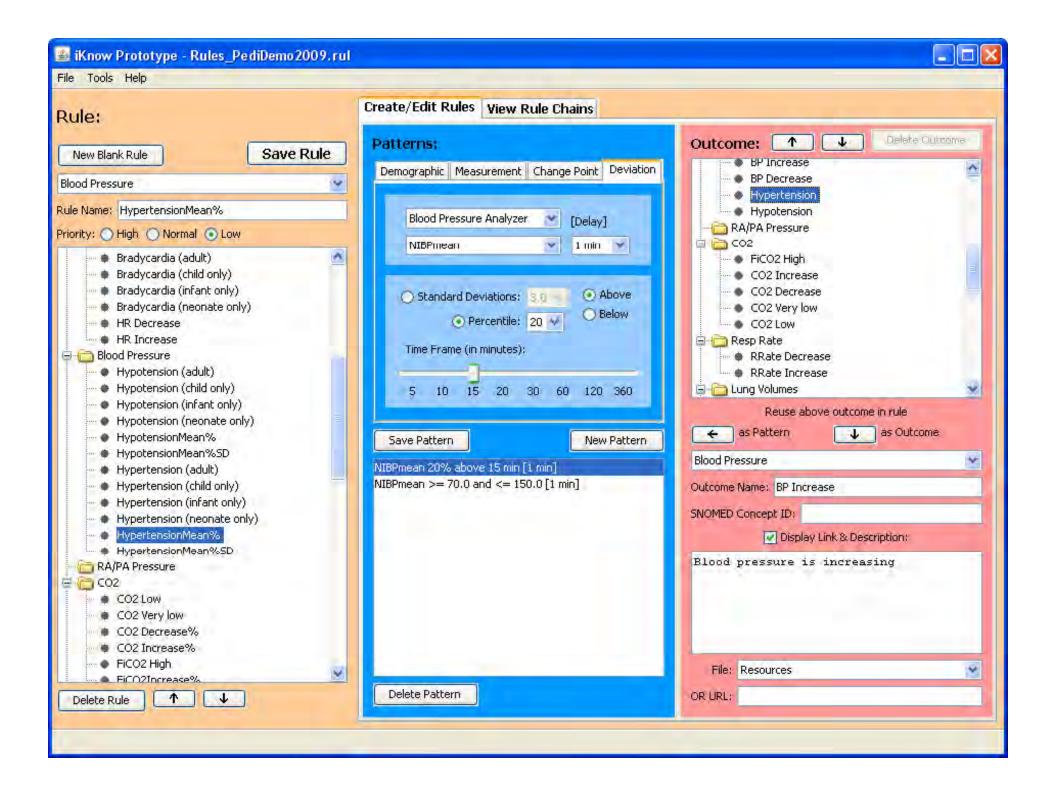


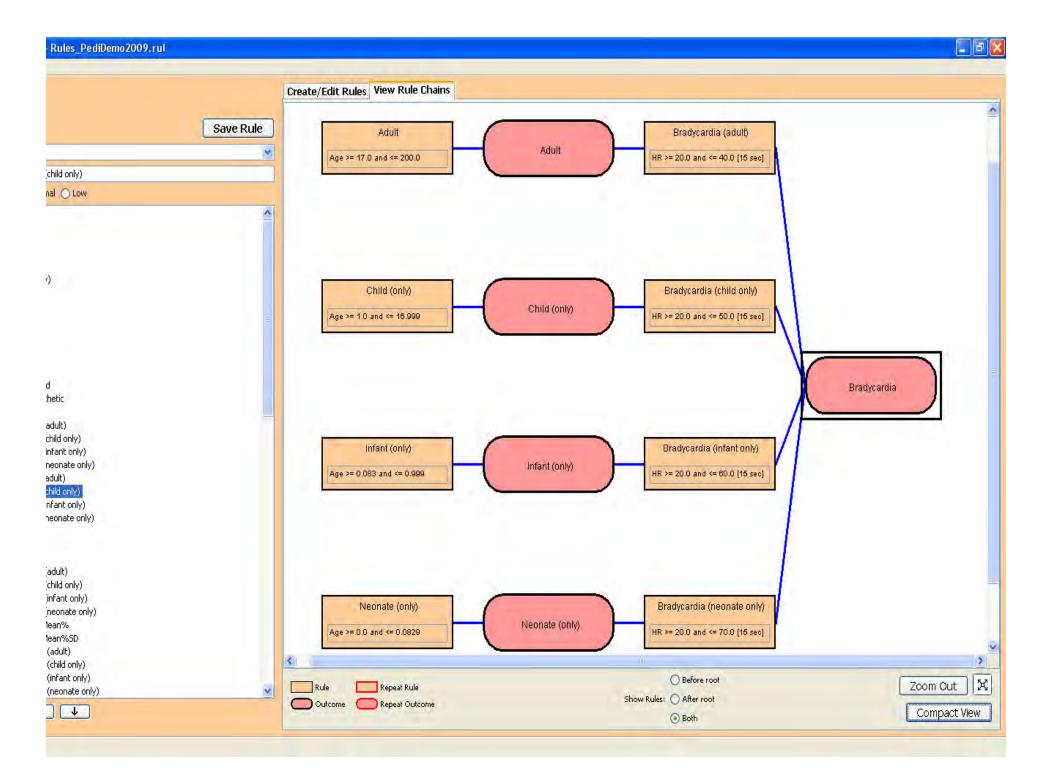


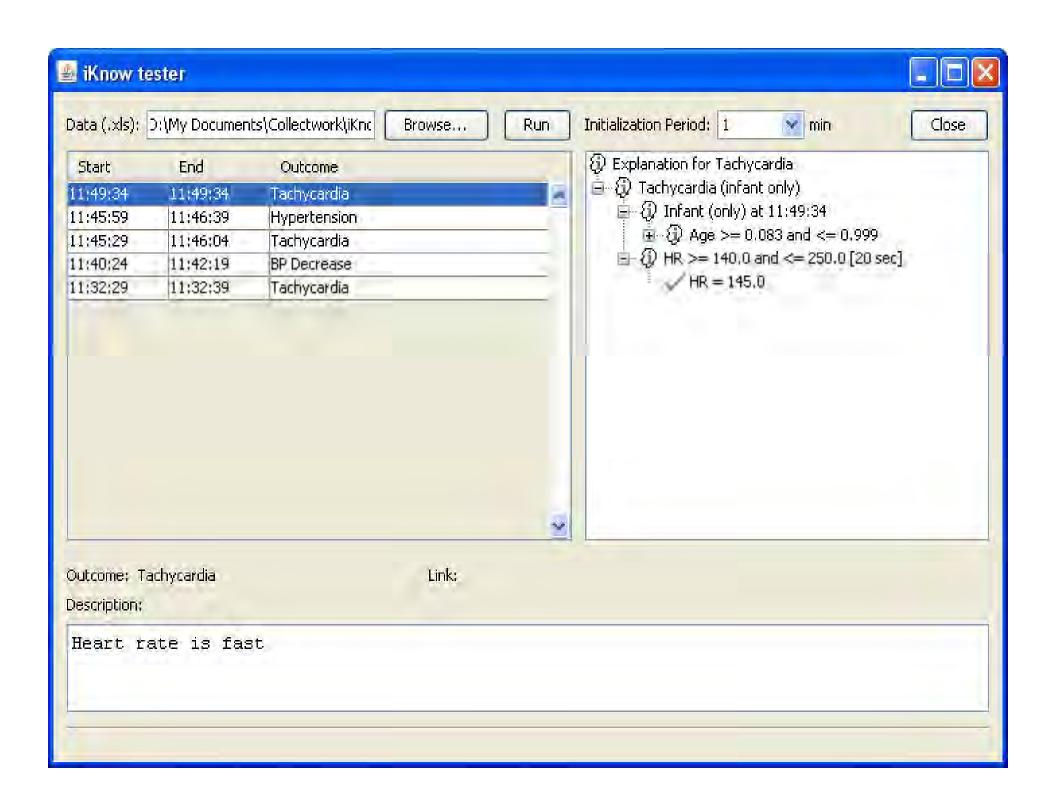












http://engineering4medicine.chii.ubc.ca/iknow/



iKnow Information

<u>Home</u> <u>Model</u> <u>FAQ</u> <u>Download</u>

Help Files

- Purpose
- Quick Start
- <u>Rule</u>
 <u>Components</u>
- Panel Descriptions
- Walkthrough
- Input and Output
- Menu items

Contact

Knowledge Authoring Tool

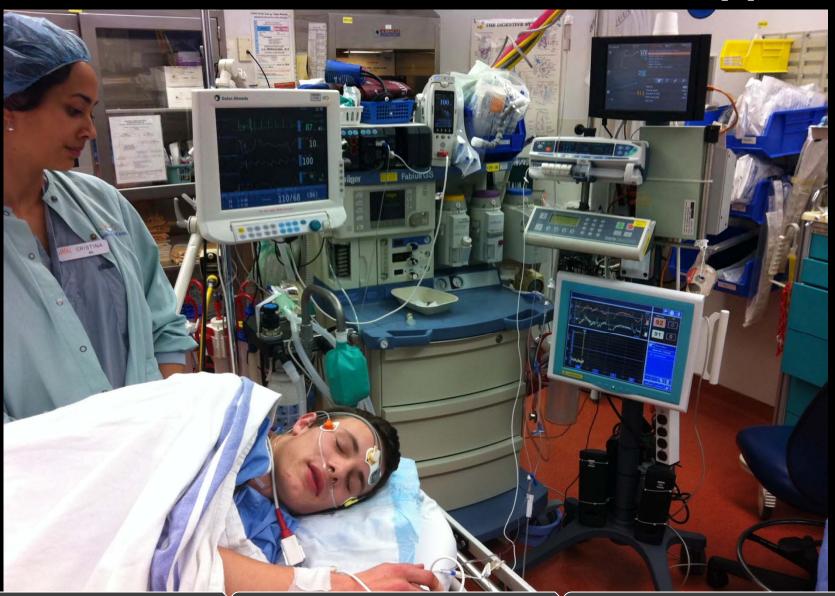
iKnow is a tool for building a knowledge base for physiological monitoring. Expert knowledge about physiological monitoring, such as is used in anesthesia or the intensive care unit, is encoded into a set of rules. These rules are used in real time by the inference engine of an expert system. iKnow is designed to be easy to use and avoid the need for a knowledge engineer for rule creation. The rules are run in real time against inputs from clinical monitoring devices.

iKnow can create a custom list of rules representing the individual clinician's knowledge or developed collaboratively by an institution or professional organization to standardize group knowledge.

The software generates programming code in a rule-based expert system language called <u>JBoss Rules</u>. The set of rules are then run, in real time at the patient's bedside, against data generated by physiological monitors. Included within the iKnow program is a testing subapplication which allows a user to test the rules output against data in an Excel file. The data in this Excel file can be edited to force the rules to fire.

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Automation is the ultimate decision support!



Cognitive Bias

Information Overload

Automation





Thanks for listening....

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